Prescription Drug Monitoring Programs: The Role of Asymmetric Information on Drug Availability and Abuse

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Abstract

The diversion of controlled prescription drugs can arise through "doctor shopping," where a patient obtains multiple prescriptions from different healthcare providers without the providers' knowledge of the other prescriptions. Prescription Drug Monitoring Programs (PDMPs) aim to address this problem of asymmetric information. In this paper, I exploit cross-state variation in PDMP implementation dates to estimate the effect of PDMPs on drug quantities and deaths. I expand upon previous work by analyzing outcomes for prescription drugs within and outside the opioid class, by considering spillovers into the illegal drug market, and by relying on high-frequency administrative data spanning the years 2000–13. I also estimate the effect of two PDMP characteristics with the potential to narrow information asymmetries among providers: direct PDMP access and required PDMP use. I find that neither PDMP implementation nor direct PDMP access had a significant effect on outcomes. These findings hold across drug classes, drug markets, and specifications. I find evidence, however, suggesting that required PDMP use reduced prescription opioid and stimulant quantities by 9% and 11%, respectively. In turn, prescription opioid and benzodiazepine deaths decreased by 9% and 13%, respectively. I also find evidence, albeit weak, suggesting that illegal drug deaths increased.
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I INTRODUCTION

Over the last decade, prescription drug abuse has become one of the largest and fastest growing drug problems in the United States.[2] In 2011, the Centers for Disease Control and Prevention classified prescription drug abuse an epidemic. That year, prescription drugs were responsible for nearly 23,000 overdose deaths, a 203% increase from 1999 levels (CDC, 2015). The expansion of insurance coverage, prescribing practices, development of new pharmaceuticals, and pharmaceutical advertisement have been proposed as contributing to the epidemic and fueling prescription drug diversion (NCHS, 2015). Prescription drugs are diverted for illegal purposes or abuse through various sources, including doctor prescriptions, medication and prescription pad theft, employee pilferage, and the Internet. Commonly diverted prescription drugs include benzodiazepines, stimulants, and especially, opioid pain relievers. Survey data suggests that doctor prescriptions are the original source of most diverted opioid pain relievers. In 2013, 23.8% of past-year non-medical users reported obtaining opioid pain relievers from at least one doctor, and 46.1% for free from a friend or relative who obtained them from at least one doctor (NSDUH, 2014).

Oftentimes doctors are unaware when a patient is abusing prescription drugs, let alone when a patient is obtaining multiple prescriptions from other providers, a practice commonly known as doctor shopping. To address information asymmetries that arise when non-medical users cannot be differentiated from medical users, most states have implemented Prescription Drug Monitoring Programs (PDMP). PDMPs are electronic databases that collect designated data on controlled substances dispensed within a state, and allow selected healthcare providers, law enforcement officials,

[2] In 2014, an estimated 6.5 million Americans aged 12 or older reported being non-medical users of prescription drugs in the past month, more than any other illicit drug with the exception of marijuana (NSDUH, 2015).

PDMP administrators, and other authorized stakeholders to identify consumption patterns that are consistent with doctor shopping.[3] The data collected generally includes the names and contact information of the patient, prescriber, and dispenser, the name and dosage of the drug, the quantity supplied, the number of authorized refills, and the method of payment.

PDMP characteristics vary widely across states. Specifically, states can differ in who may access the database (e.g. prescribers, dispensers, law enforcement), in the agency that administers the PDMP (e.g. department of health, pharmacy boards), in the controlled substances (CS) that are reported (e.g. some don't monitor CS-V), in the timeliness of data reporting (e.g. daily, weekly), in how to identify and investigate cases of potential doctor shoppers (e.g. reactive, proactive), and in whether prescribers are required to query the database (Finklea et al., 2014).[4] The evolution of PDMPs has also varied across states over time. For instance, originally several states implemented paper-based PDMPs but eventually these and others shifted to electronic-based PDMPs. Moreover, the date of PDMP *implementation* did not always coincide with the date of PDMP *access* to healthcare providers.[5] More recently, a growing number of states have enacted laws *requiring* healthcare providers to query the PDMP under certain circumstances (TTAC, 2016; NAMSDL, 2014).

The question of PDMP effectiveness is key as this policy tool is considered a promising approach against prescription drug abuse and is listed as a main strat-

[3]Note that PDMP access varies by state.

[4]States may be classified as reactive or proactive depending on their approach to identifying and investigating cases of potential diversion. Reactive states generate reports in response to a request by authorized parties, while proactive states generate unsolicited reports whenever suspicious behavior is detected (Finklea et al., 2014).

[5]The date of PDMP *implementation* is defined as the date when dispensers started reporting CS transactions to the database. The date of PDMP *access* to healthcare providers is defined as the date when dispensers and prescribers were granted access to patient reports. Access could be *direct* (e.g. providers can obtain patient reports by querying the PDMP directly) or *indirect* (e.g. providers can obtain patient reports by submitting a request to PDMP administrators).

egy in the federal government's Prescription Drug Abuse Prevention Plan.[6] At the same time, however, PDMPs can be costly to operate and their utilization in healthcare settings can potentially disrupt patient-provider interactions, the flow of treatment delivery, and ultimately, affect patient outcomes.[7] In this paper, I employ a quasi-experimental design that exploits cross-state variation in the timing of PDMP implementation to estimate the effect of PDMPs on drug quantities and overdose deaths. I also estimate the effect of two PDMP characteristics with the potential to narrow information asymmetries in healthcare settings. Specifically, I consider direct PDMP access and required PDMP use among healthcare providers. PDMP implementation is defined as the time when PDMP operations began,[8] direct PDMP access is defined as the time when healthcare providers were granted firsthand access to query the database,[9] and required PDMP use is defined as the time when laws requiring healthcare providers to query the database became effective. A successful PDMP should reduce prescription drug abuse and its associated harms. However, an unintended consequence might be substitution toward illegally produced drugs. To identify spillovers into the illegal drug market, this paper also estimates the effect of PDMPs on heroin and cocaine abuse. The outcomes of interest include drug quantities from the Drug Enforcement Administration's Automation of Reports and Consolidated Orders System and overdose deaths from the National Vital Statistics System Mortality Files. Data on outcomes are based on administrative sources, represent a near census of events, are high frequency, and span the years 2000-2013.

[6](ONDCP, 2011)

[7]PDMP costs vary, with startup costs ranging from $450,000 to $1.5 million and annual operating costs ranging from $125,000 to $1.0 million (Finklea et al., 2014).

[8]The date a PDMP became *operational* is defined as the date when data collection began (e.g. when dispensers started reporting CS transactions to the database). Note that at this time, PDMP administrators had access to the database, and depending on the state, also did other stakeholders such as law enforcement, prescribers, or dispensers.

[9]Prior to direct PDMP access, healthcare providers either had no access or had indirect access (e.g. providers could submit a request to PDMP administrators to obtain reports for a given patient).

Previous studies on PDMPs' effectiveness at the national level report mixed results (Curtis et al., 2006; Reifler et al., 2012; Reisman et al., 2009; Bao et al., 2016; Kilby, 2015; Patrick et al., 2016; Paulozzi et al., 2011; Brady et al., 2014; Radakrishnan, 2014). While some find that PDMPs can reduce prescription drug availability and abuse, others find no effect. These mixed results are likely explained by differences in research design across studies. Specifically, previous PDMP studies differ in terms of data, sample window (and thus, treatment group),[10] outcomes of interest, identification strategy, econometric model, and PDMP dates. Early PDMP studies are observational and compare outcomes in states with a PDMP to those in states without a PDMP. As PDMP implementation is not randomly assigned, treated states likely differ from control states in multiple dimensions, making it impossible to establish causality. Two recently published studies (Bao et al., 2016; Patrick et al., 2016), alike this paper, have attempted to overcome this limitation by exploiting cross-state variation in the timing of PDMP implementation.[11] Using survey data,[12] a difference-in-differences approach, and focusing on treated states only, Bao et al. (2016) concluded that PDMP access was associated with nearly a 30 percent reduction in the proportion of Schedule II opioid prescribing, but with a limited effect on overall opioid prescribing. Using mortality data, an interrupted time series approach, and focusing on treated states only, Patrick et al. (2016) concluded that PDMP implementation was associated with a reduction of 1.12 opioid-related overdose deaths per 100,000 population in the year after implementation. Neither of these studies,

[10]Since PDMP characteristics and the timing of PDMP implementation varies by state, differences in the treatment group population arising from differences in the sample window across studies might also explain mixed findings.

[11]Kilby (2015) and Radakrishnan (2014) are two additional working papers that implement a quasi-experimental design to address the question of PDMP implementation but this work does not focus on PDMP characteristics nor on drugs outside the opioid class, and define PDMP operations differently. For instance, Radakrishnan (2014) focuses on the time a PDMP became electronic which I see as complementing evidence.

[12]They use The National Ambulatory Medical Care Survey (NAMCS) and noted that in 2010, NAMCS had an unadjusted physician response rate of 58 percent.

however, provide evidence supporting that the identifying assumptions of parallel trends and no-policy endogeneity hold, nor test the robustness of their findings to the inclusion of state-specific linear trends. Moreover, Patrick et al. (2016) do not control for year fixed effects in regression specifications, and thus, fail to account for nation-wide interventions that may bias the results.

In an effort to provide more robust and comprehensive evidence of the effect of PDMPs on drug quantities and overdose deaths, I build upon previous studies and overcome some of their limitations. One such limitation is that most previous studies have ignored heterogeneity in PDMP characteristics.[13] I address this limitation by exploiting not only time and geographic variation in PDMP implementation, but also in direct PDMP access and in required PDMP use. A second limitation is that most previous studies have constrained their analysis to prescription opioid-related outcomes. Yet, there are other highly addictive prescription drugs that should be directly affected by PDMPs and other highly addictive illegally produced drugs that could be indirectly affected by PDMPs. I address this limitation by analyzing outcomes for several commonly abused prescription and illegal drugs. These include prescription opioids, prescription stimulants, prescription benzodiazepines, heroin, and cocaine. Finally, I provide more robust evidence of the effect of PDMPs by estimating a difference-in-differences specification and testing the sensitivity of the findings to a battery of robustness checks that include changes in control variables (e.g. state-specific linear trends), in time windows (e.g. all years, +/- 2 years), in modeling approaches (e.g. linear model with log-transformed outcomes, generalized linear model with Poisson distribution and log link function), and the exclusion of outlier states with concurrent interventions. Moreover, I provide parametric and non-parametric graphical evidence based on an event study approach to allow the

[13] A notable exception is Patrick et al. (2016) which considers some program characteristics.

reader to visually assess the credibility of the estimates.

I find that PDMP implementation alone had no significant effect on drug quantities or overdose deaths. Moreover, I find that direct PDMP access among healthcare providers also had no significant effect on outcomes. These findings hold across drug classes (e.g. opioids, benzodiazepines, and stimulants), drug markets (e.g. legal and illegal), modeling approaches, and control variables. I find evidence, however, suggesting that required PDMP use reduced prescription opioid and stimulant quantities by 9% and 11%, respectively. In turn, overdose deaths involving prescription opioids and benzodiazepines decreased by 9% and 13%, respectively. These results are robust to the modeling approach and hold across drug classes, which strengthens their credibility as many required PDMP use laws target prescribing across all prescription drugs in schedules II-IV and not only those in the opioid class. I also find evidence, albeit weak, that illegal drug overdose deaths increased. Specifically, estimates based on the linear model with log-transformed outcome suggest that overdose deaths involving heroin and cocaine increased by 40% and 12%, respectively. While cocaine's estimate is robust to the modeling approach, heroin's estimate is not. Estimates based on the generalized linear model with Poisson distribution and log link function suggest that overdose deaths involving heroin and cocaine increased by 11% and 15%, respectively.

One possible explanation for the lack of significant effects of PDMP implementation and direct PDMP access and the presence of significant effects of required PDMP use is inconsistent PDMP utilization among healthcare providers. Physicians report that the time and complexity required to access relevant information are the main barriers that prevent them from checking the PDMP on every patient (Perrone et al., 2012). Laws requiring healthcare providers to use the PDMP under certain circumstances address this issue of inconsistent utilization and thus, can be

more successful at reducing prescription drug diversion and abuse. Results from this study uncover the importance of heterogeneity when assessing PDMP effectiveness and suggest that required PDMP use can be a promising policy approach against prescription drug diversion and abuse. Despite these encouraging results, I do find some evidence of potential offsetting effects from spillovers into the illegal drug market. Future studies should further explore the potential benefits and costs of these laws as more states continue to implement them.

II EMPIRICAL STRATEGY

II.*A* *Data Sources*

This paper examines prescription drug quantities and overdose deaths. Outcomes are drawn from administrative sources, represent a near census of events, are high frequency, and span the period 2000-13. The unit of analysis is a state-year-quarter.

Drug quantities are drawn from the Drug Enforcement Administration's Automation of Reports and Consolidated Orders System (ARCOS), a drug reporting system that monitors the flow of controlled substances from their point of manufacture through commercial distribution channels to point of sale or distribution at the retail level. ARCOS measures total grams purchased by pharmacies, hospitals, practitioners, mid-level practitioners, narcotic treatment programs, and teaching institutions, and thus, captures the legal supply of prescription drugs at the provider level before it reaches consumers.[14] This study specifically relies on ARCOS Re-

[14]ARCOS data will not reflect illegal trade of prescription drugs across state lines. Specifically, suppose that legal suppliers in state A and B purchased 10 and 15 grams of oxycodone, respectively. Moreover, suppose that consumers in state A smuggled 2 grams of oxycodone from state B, so that total supply available for consumption in state A and B is actually 12 and 13 grams, respectively. In this example, ARCOS will report 10 grams for state A and 15 grams for state B. As this example shows, however, supply in a state can reflect demand from out-of-state residents.

port 2, where the unit of observation is a state, quarter, and active ingredient (for substances in schedules I & II and selected substances in schedule III). Active ingredients are categorized into two drug classes of interest: opioids and stimulants. The opioid class includes the active ingredients codeine, fentanyl, hydrocodone, hydromorphone, meperidine, morphine, oxycodone, methadone, and oxymorphone. The stimulant class includes the active ingredients amphetamine and methylphenidate. To make active ingredients comparable, grams in each drug class are adjusted for potency as described in Table 4 in the Appendix, with opioid grams converted into oxycodone potency units and stimulant grams converted into amphetamine potency units. In three instances, an outlier is dropped and inputed with the average value in the previous and following quarter. Specifically, South Dakota and South Carolina display a one time jump in fentanyl grams in the second quarter of 2011 and in the first quarter of 2013, respectively. Also, Louisiana displays a one time jump in grams in the fourth quarter of 2007.

Overdose deaths are drawn from the National Vital Statistics System's (NVSS) restricted use Mortality Files. Mortality Files are based on information abstracted from death certificates and provide multiple cause of death for nearly all deaths occurring within the United States. The underlying cause of death is defined following previous reports by the National Center on Health Statistics and the CDC WONDER. Specifically, totals include deaths due to unintentional drug poisoning (X40-X44), suicide drug poisoning (X60-X64), homicide drug poisoning (X85), or drug poisoning of undetermined intent (Y10-Y14), and are defined as in the International Classification of Diseases, 10th Revision. Opioid pain relievers are defined as (T40.2-T40.4), Benzodiazepines as (T42.4), Cocaine as (T40.5), and Heroin as (T40.1). NVSS Mortality Files have several strengths, including detailed identifiers (e.g. county, month, and type of drug), nearly universal coverage, and considerable

uniformity in content and format across states (CDC, 1989). Nonetheless, this data also have several limitations worth noting. Specifically, previous work has found that cause and manner of death are not always reported in a consistent or accurate fashion. This inconsistency generally arises because of difficulties in reaching an agreement regarding the cause of death under certain scenarios and because of failure to complete items correctly due to lack of proper training (Swain et al., 2005; Smith et al., 2001). Another limitation specific to drug overdoses is that approximately 25% of certificates do not specify which type of drugs were involved in a death, an omission either due to lack of toxicological tests or due to failure to record the results of toxicological tests on the certificate. The degree to which type of drugs are unspecified on death certificates can vary across states (Wysowski, 2007; Jones et al., 2013).

The dates of PDMP implementation were originally collected by contacting PDMP administrators in all states or by reading the documentation in PDMP websites. These dates were then compared with those collected by the National Alliance for Model State Laws (NAMSL),[15] Brandeis University's PDMP Training and Technical Assistance Center (TTAC),[16] and The Office of the National Coordinator for Health Information Technology (ONCHIT).[17] Mismatches in dates were identified across all sources for certain states. These mismatches were further investigated by contacting PDMP administrators or by reading the documentation in PDMP websites and other official sources a second time around. Mismatched dates were determined based on this iterative process and on consensus among NAMSL, TTAC, and ONCHIT.[18]

[15] http://www.namsdl.org/library/1667DC6B-65BE-F4BB-AB7F08135A3A7174/

[16] http://www.pdmpassist.org/content/state-profiles

[17] https://www.healthit.gov

[18] Mismatches in dates were more common among early implementing states. During the sample window 2000-13, the PDMP implementation dates used in this study are nearly identical to those listed by TTAC. The only exception is the state of Virginia, which implemented a pilot program in 2003 and a full program in 2006. TTAC lists 2003, but I use 2006. Results are robust to the assignment of either date.

The dates of direct PDMP access were also originally collected by contacting PDMP administrators in all states or by reading the documentation in PDMP websites. These dates were then compared with those collected by NAMSL.[19] Mismatches in dates were identified for certain states. These mismatches were further investigated by contacting PDMP administrators or by reading the documentation in PDMP websites and other official sources a second time around. Mismatches in dates generally occurred because NAMSL collected the dates of PDMP access regardless of whether such access was direct (e.g. firsthand access to patient reports) or indirect (e.g. make a request to a PDMP administrator and wait for them to send a patient report), as where this study collected the dates of direct PDMP access.

Finally, states with laws requiring PDMP use and their respective effective dates were identified through documentation prepared by NAMSL, TTAC, and The Policy Surveillance Program (PSP) at Temple University (NAMSDL, 2011, 2014; TTAC, 2016; PSP, 2011). PSP documented states with required PDMP use laws and the years in which the laws became effective as of 2011. NAMSL documented states with required PDMP use laws and the text of relevant statutes as of 2011 and as of 2014. TTAC documented states with required PDMP use laws, the year of the laws, and whether the laws were "subjective" as of 2016. Subjective laws were those for which "required PDMP use" remained at the discretion of the provider, and thus, did not represent an actual requirement. For the purpose of this study, I excluded states identified as having "subjective" laws. Mismatches in effective dates were identified across all sources for some states (see Table 7 in the Appendix for details).[20] Mismatched effective dates were determined in three ways: (1) by

[19] http://www.namsdl.org/library/1667DC6B-65BE-F4BB-AB7F08135A3A7174/

[20] This is not surprising as in some cases, the wording, source, scope, and stringency of the law varied across states or evolved over time within a state, making it challenging to establish an effective date or whether an actual requirement existed.

contacting PDMP administrators in these states or by reading the documentation listed in PDMP websites; (2) by conducting a google search based on the names of the relevant statutes identified by NAMSL; and (3) by comparing dates identified through approaches (1) and (2) with those identified by TTAC and PSP. In order to provide comprehensive evidence, I also report estimates based on an analysis that accounts for heterogeneity across state laws (see Tables 9 and 10 in the Appendix).

Tables 5, 6 and 7 in the Appendix report the dates of PDMP implementation, direct PDMP access, and required PDMP use collected by the author and other sources. Figure 1 plots the dates of PDMP implementation, direct PDMP access, and required PDMP use.

II.*B* *Econometric Approach*

The empirical strategy is to exploit variation in the timing, geographic location, and policy dimensions generated by states' implementation of PDMPs. Equation 1 is the baseline econometric specification where the unit of analysis is indexed by state s and year-quarter t. $PDMP_{st}$ identifies the time of PDMP implementation and is equal to one if state s operated a PDMP in year-quarter t and zero otherwise. X_{st} identifies a PDMP characteristic with the potential to narrow information asymmetries and is equal to one if state s adopted such characteristic in year-quarter t and zero otherwise. S_s are state fixed effects, T_t are year fixed effects, Q_t are quarter fixed effects, and $ln(P_{st})$ is the log of population.[21] $ln(Y_{st})$ is the log of measures of prescription drug quantities or overdose deaths.[22] To avoid losing observations with count zero, I added 1 to all outcomes. As an alternative to this log transformation approach, I

[21] State-year population estimates were drawn from the Census' American Fact Finder for the years 2000-13.

[22] I found that in general, "log outcomes" do a better job at satisfying the parallel trends assumption than "per capita outcomes", and so, I adopted this data transformation approach.

also estimated a generalized linear model that assumed a Poisson distribution with log link function. In all instances, standard errors were clustered at the state level.[23]

$$ln(Y_{st}) = \alpha_0 + \alpha_1 PDMP_{st} + \alpha_2 X_{st} + \alpha_3 ln(P_{st}) + S_s + T_t + Q_t + \epsilon_{st} \quad (1)$$

$$ln(Y_{st}) = \beta_0 + \beta_1 PDMP_{st} + \beta_2 X_{st} + \beta_3 ln(P_{st}) + Trends_{st} + S_s + T_t + Q_t + \epsilon_{st} \quad (2)$$

$$ln(Y_{st}) = \alpha_0 + \sum_{j=-m}^{q} \hat{\alpha_j} D_{st}(j = t - k) + \alpha_3 ln(P_{st}) + S_s + T_t + Q_t + \epsilon_{st} \quad (3)$$

$$ln(Y_{st}) = \beta_0 + \sum_{j=-m}^{q} \hat{\beta_j} D_{st}(j = t - k) + \beta_3 ln(P_{st}) + Trends_{st} + S_s + T_t + Q_t + \epsilon_{st} \quad (4)$$

Estimates from Equation 1 are only valid under the assumptions of no policy endogeneity and parallel trends. To examine the sensitivity of α_1, estimates based on Equation 2, which includes state-specific linear time trends $Trends_{st}$, are also reported. Despite Equation 2 being a potentially more robust specification, threats to identification still remain as trends in outcomes might be correlated with PDMP implementation in ways that state-specific linear time trends may fail to capture. To assess the credibility of the findings and determine whether there is a dynamic treatment effect, estimates from Equations 3 and 4 are plotted. This analysis is based on an event study approach and controls for m leads and q lags of the treatment, captured in the dummy variables $D_{st}(j = t - k)$, where k is the time of PDMP implementation in state s. The reference group is $j = 0$, the period right before PDMP implementation. A test validating the identifying assumptions is if the coefficient

[23]For robustness, I also estimated block bootstrapped standard errors (not shown). Block bootstrapped standard standard errors were only slightly larger and did not affect conclusions from the study.

of $D_{st}(j = t - k)$ is zero for all $j < 0$ (this need not be the case for $j > 0$). More generally, detecting a trend or an irregular jump prior to PDMP implementation should raise concerns regarding the validity of α_1 and β_1.

The issue of policy endogeneity is further addressed by dropping the state of Florida from the analysis as its inclusion may result in misleading evidence for some outcomes.[24] Specifically, Florida was at the center of the opioid epidemic in the late 2000s, was an extreme outlier in trends and levels, and was subject to aggressive enforcement actions and pain clinic regulation near the time of PDMP implementation (Meinhofer, 2016). As these concurrent interventions resulted in substantial declines in opioid and benzodiazepine supply, even prior to PDMP implementation, excluding Florida will reduce bias and result in more informative estimates.

A different source of bias may arise from compositional effects as the staggered implementation of PDMPs implies that not all treated states are observed throughout the same lags and leads. Because this potential issue can be exacerbated with lag and lead extreme values, estimates based on +/- 2 years since PDMP implementation, direct PDMP access, and required PDMP use are also reported as a robustness check. Note, however, that under the presence of a dynamic treatment effect, differences between "all years" and "+/- 2 years" estimates will likely be detected and should not be interpreted as resulting from compositional effects. The event study plots can be informative when making this assessment.

[24] This is especially true for outcomes based on ARCOS data.

III RESULTS

III.*A* *Non-Parametric Graphical Evidence*

This section provides non-parametric evidence of the effect of PDMP implementation and PDMP characteristics on drug quantities and overdose deaths by plotting the raw data (see Figures 2 and 3).[25] Additional non-parametric evidence based on locally weighted regressions can be found in the Appendix (see Figures 6 and 7). Outcomes for treated states during the sample period 2000-13 are centered at the time of treatment implementation and plotted for the periods before and after.

Figure 2 plots outcomes centered at the time of PDMP implementation. The appearance of such plots can be affected by compositional effects as not all treated states are observed during all periods before and after PDMP implementation.[26] To assess the importance of this issue, plots are based on a balanced panel of treated states at different before and after time windows, namely +/- 1, +/- 2, and +/- 3 years.[27] There is no evidence of a trend or a level break in stimulant or opioid grams per 100,000 persons at the time of PDMP implementation nor in the years that follow. Similarly, there is no evidence of a trend or a level break in opioid or benzodiazepine deaths per 100,000 persons at the time of PDMP implementation nor in the years that follow. Heroin and cocaine deaths per 100,000 persons display somewhat conflicting evidence. Specifically, heroin deaths appear to increase after PDMP implementation, while cocaine deaths appear to decrease. It is unclear whether this effect can be attributed to PDMP implementation or to other nation-wide illegal drug market

[25] see Figure8 in the Appendix for a plot of opioid deaths per opioid grams.

[26] This is especially true after PDMP implementation as several states adopted the program in the early 2010s.

[27] Note that under this construction, the number of balanced states decreases as the time window increases. See Table 5 for the states included in each time window.

factors (e.g. increase in heroin availability nation-wide in the early 2010s). Regression analysis in Section III.***B*** will help alleviate these concerns by allowing to control for year fixed-effects. It is worth noting that in some instances compositional effects appear to matter, especially beyond the +/- 2 year time window, as the slope and the level of remaining treated states changes.[28]

Figure 3 plots outcomes centered at the time of PDMP implementation, direct PDMP access, and required PDMP use.[29] While there is no evidence of an effect of PDMP implementation or direct PDMP access on drug quantities and overdose deaths, there appears to be some evidence of an effect of required PDMP use on outcomes. Specifically, prescription opioid and benzodiazepine-related outcomes appear to decrease while heroin-related outcomes appear to increase after laws requiring PDMP use become effective. Again, it is unclear whether this effect can be attributed to required PDMP use or to other nation-wide factors, but regression analysis in Section III.***B*** will help alleviate these concerns by allowing to control for year fixed-effects.

III.*B* *Regression Analysis*

The following sections report estimates of the effect of PDMP implementation and PDMP characteristics on drug quantities and overdose deaths. Section III.***B***.1 reports estimates of the effect of PDMP implementation on outcomes (e.g. dispensing healthcare providers start reporting controlled substance transactions to the database). Section III.***B***.2 reports estimates of the effect of PDMP characteristics

[28] In the sample, outcomes for nearly all states are observed up to 3 years before PDMP implementation, but outcomes for states implementing after 2010 are not fully observed up to 3 years after PDMP implementation (recall that the sample window ends in 2013).

[29] Note that unlike Figure 2, these plots are not based on a balanced panel of states but include all states observed at some point during the +/- 2 time window.

on outcomes. PDMP characteristics include direct PDMP access (e.g. dispensers and/or prescribers can query the database directly and on a voluntary basis) and required PDMP use (e.g. dispensers and/or prescribers must query the database under certain circumstances).

III.*B*.1 *PDMP Implementation*

This section reports estimates of the effect of PDMP implementation on drug quantities and overdose deaths (see Table 1). Drug quantities are measured in grams and are drawn from ARCOS Report 2, while overdose deaths are drawn from NVSS Mortality Files. Main estimates in Table 1 are based on the log transformation of the outcome as in Equations 1 and 2. To assess the credibility of main estimates and determine whether there is a dynamic effect, graphical evidence based on the event study approach in Equations 3 and 4 is presented (see Figure 4). As a robustness check, estimates based on the generalized linear model with Poisson distribution and log link function are also presented.

Panel A in Table 1 reports estimates of the effect of PDMP implementation on grams for prescription drugs in the opioid and stimulant classes. Regardless of the specification, time window, or modeling approach, I find no evidence of a significant effect of PDMP implementation on outcomes. Panel B in Table 1 reports estimates of the effect of PDMP implementation on overdose deaths with a mention of prescription drugs in the opioid and benzodiazepine classes. To detect for potential spillovers into the illegal drug market, Panel B also reports estimates for overdose deaths with a mention of heroin and cocaine. As with grams, I find no significant effect of PDMP implementation on overdose deaths. Figure 4 provides graphical evidence based on the event study approach. The identifying assumptions appear to hold and there is

no evidence of a dynamic effect. A notable exception are heroin deaths, which exhibit a negative and statistically significant effect (at the 10% level). This effect, however, is not robust to the inclusion of state-specific linear trends and is not detected in the first two years post PDMP implementation nor in the generalized linear model.

All things considered, the parametric evidence suggests that PDMP implementation alone had no effect on drug quantities or overdose deaths. These findings coincide with non-parametric graphical evidence (see Figures 2, 3, 6 and 7). Despite these discouraging results, PDMPs vary in many dimensions and specific program characteristics with the potential to reduce information asymmetries such as direct PDMP access or required PDMP use may yield more promising outcomes. Section III.***B***.2 explores this possibility in depth.

III.***B***.2 *PDMP Characteristics*

This section reports estimates of the effect of PDMP characteristics on drug quantities and overdose deaths (see Tables 2 and 3). PDMP implementation is included as a control variable in all specifications. Main estimates in Tables 2 and 3 are based on the log transformation of the outcome as in Equation 2. As a robustness check, estimates based on the generalized linear model with Poisson distribution and log link function are also reported. To assess the credibility of main estimates and determine whether there is a dynamic effect, graphical evidence based on the event study approach in Equation 4 is presented.

Table 2 reports estimates of the effect of direct PDMP access on drug grams (Panel A) and overdose deaths (Panel B). Regardless of the drug class, drug market, modeling approach, or time window, I find no evidence that direct PDMP access had a significant effect on outcomes. The absence of a significant effect is surprising

considering that granting healthcare providers direct PDMP access should improve the timeliness of obtaining patient reports and, thus, increase the probability of identifying doctor shoppers before prescribing or dispensing decisions are made.

Table 3 reports estimates of the effect of required PDMP use on drug grams (Panel A) and overdose deaths (Panel B). I find statistically significant evidence suggesting that required PDMP use reduced opioid grams by 9%. The coefficient on stimulant grams (11%) is also statistically significant, negative, and of a similar magnitude as that on opioid grams. Estimates from the generalized linear model are also statistically significant and even slightly more negative. I also find some evidence of reductions in prescription drug overdose deaths. Specifically, I find that required PDMP use reduced prescription opioid and benzodiazepine deaths by 9% and 13%, although these "all years" effects are not statistically significant. Nonetheless, when I break the effect into that in the first two years ($+/-$ 2 $Years$) and that in remaining years (not shown), I find a statistically significant decline of 13% for opioids and 17% for benzodiazepines. Estimates from the generalized linear model are of similar magnitude and statistically significant, even for "all years" effects. Figure 5 provides graphical evidence based on the event study approach. The identifying assumptions appear to hold and the effects are evident from the plots. The fact that I find an effect for all drug classes (opioids, stimulants, and benzodiazepines) strengthens the credibility of the estimates as many states implemented laws that targeted prescribing across all prescription drugs in schedules II-IV and not only those in the opioid class.[30] Tables 9 and 10 in the Appendix consider heterogeneity in the scope and evolution of required PDMP use laws.[31]

[30] An effect for other substances might also be found due to co-abuse with opioids.

[31] With a few exceptions, including states with "subjective" required PDMP use laws into the treatment group only slightly attenuates the magnitude and statistical significance of the estimates. Conclusions from the main analysis hold under this alternative treatment group.

The implementation of required PDMP use laws may result in spillovers into the illegal drug market. To examine this possibility, estimates for overdose deaths with a mention of opioid drug heroin and stimulant drug cocaine are reported. The coefficients on heroin (40%) and cocaine (12%) are both positive, suggesting that substitution towards illegal drugs took place. This is not surprising as both, prescription drugs in the opioid and stimulant classes displayed declines in grams after required use laws became effective. While the coefficient on cocaine appears credible, the coefficient on heroin appears less credible and thus, should be interpreted with caution. Specifically, Figure 5 reveals somewhat of an upward trend in heroin deaths even prior to the implementation of required use laws (although these dummies are insignificant). Moreover, the coefficient on heroin from the generalized linear model is statistically insignificant and of substantially smaller magnitude as that from the log transformed outcome. The implementation of required PDMP use laws may also result in spillovers into non-implementing states. To examine this possibility, spillovers into neighboring states are considered (see Table 8 in the Appendix). I find some evidence of spillovers for grams but not for overdose deaths.

IV CONCLUSION

I find that PDMP implementation alone had no significant effect on prescription drug quantities and overdose deaths. These findings hold across drug classes, drug markets, time windows, modeling approaches, and control variables. I also find that direct PDMP access had no significant effect on outcomes, which is surprising considering this policy should allow healthcare providers to identify doctor shoppers in a more timely fashion and before any prescribing or dispensing takes place. I do find evidence, however, suggesting that required PDMP use can reduce prescription drug

quantities and overdose deaths across different drug classes (e.g. opioids, stimulants, benzodiazepines). A possible explanation for these findings is inconsistent PDMP utilization by healthcare providers, an issue specifically addressed by laws requiring providers to query the PDMP under certain circumstances.

Results from this study suggest that required PDMP use can be a promising approach against prescription drug diversion and abuse. Results from this study also uncover the importance of heterogeneity when assessing PDMP effectiveness. Despite these encouraging results, I do find evidence of potential offsetting effects from spillovers into the illegal drug market. Specifically, there appears to be some substitution towards cocaine and heroin, although evidence for the latter is less compelling and should be interpreted with caution. These findings for the market of illegally produced drugs coincide with recent increases in overdose deaths with a mention of heroin and, to a lesser extent, cocaine nationwide (Hedegaard et al., 2017; Jones et al., 2015), which some researchers propose have been fueled by the very same policies designed to address diversion and inappropriate prescribing. For instance, some researchers have claimed that OxyContin's reformulation resulted in increases in overdose deaths with a mention of heroin (Cicero et al., 2012). There is, however, debate regarding this issue (Compton et al., 2016). Future research should further explore the potential benefits and costs of laws requiring PDMP use among healthcare providers, especially as more states continue to implement them.

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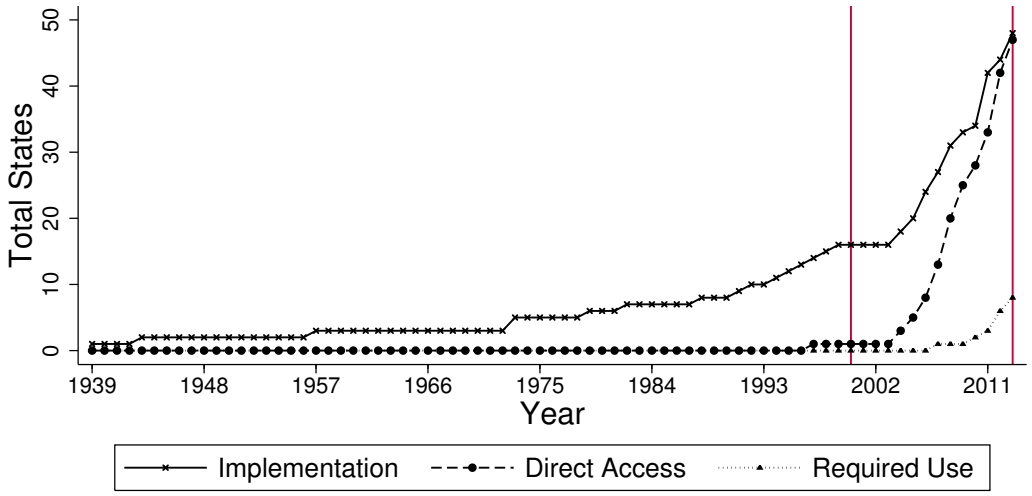

Figure 1: PDMP Key Dates as of 2013

Notes: Figure is constructed using author's tabulations of PDMP administrative data (see Tables 5, 6, and 7 in the Appendix). The vertical lines enclose the sample period of this study 2000-2013.

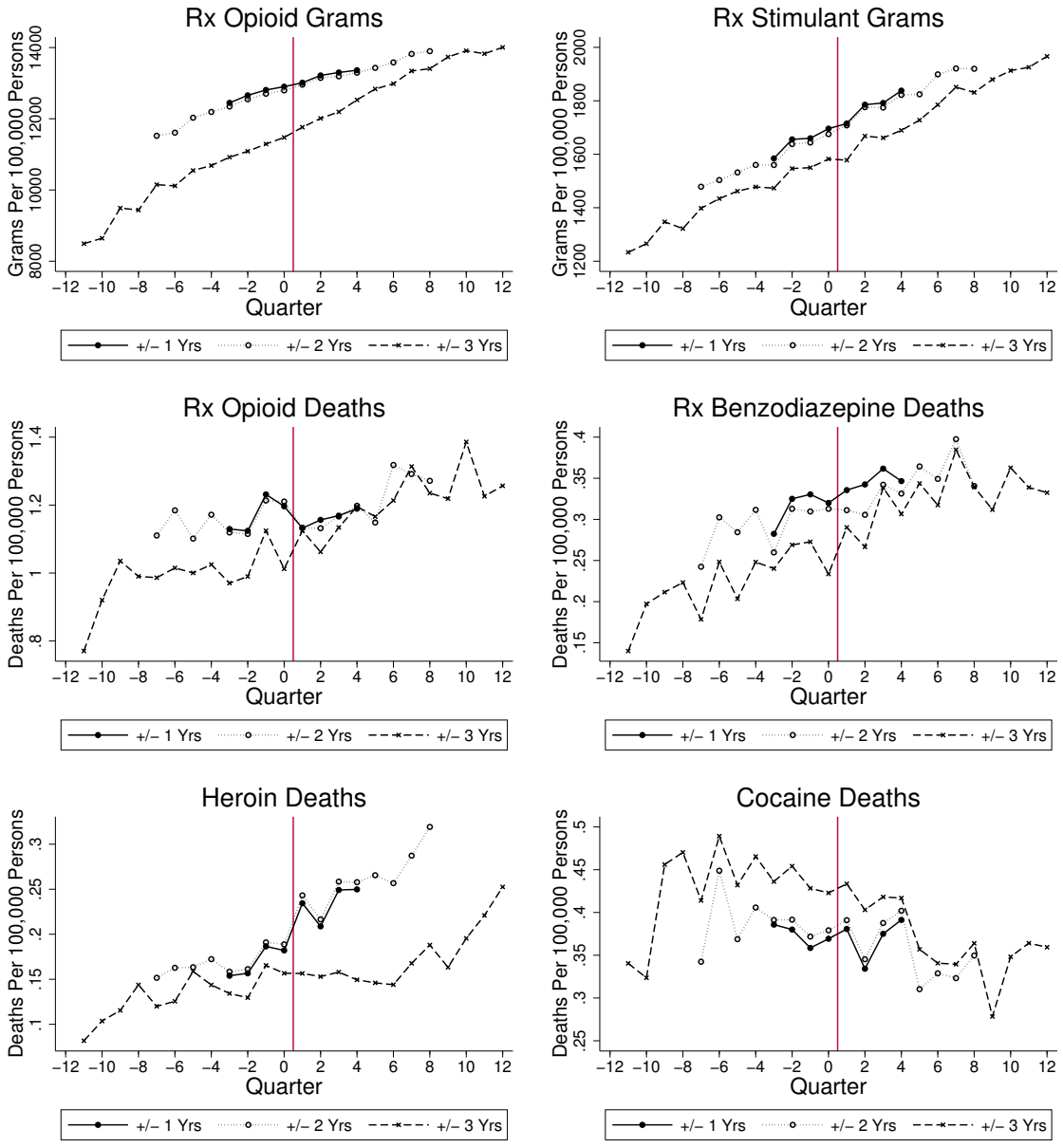

Figure 2: Effect of PDMP Implementation (2000-2013)

Notes: Drug deaths are drawn from NVSS Mortality Files and drug grams are drawn from ARCOS (see Section II.***A*** for details). Outcomes are divided by 2010 population estimates. Grams are adjusted for potency (see Table 4 in the Appendix). See Section II.***A*** for the active ingredients or ICD-10 codes in each drug class. Graphs are based on a balanced panel of treated states at different pre/post time windows. Florida is dropped (see Section II.***B***).

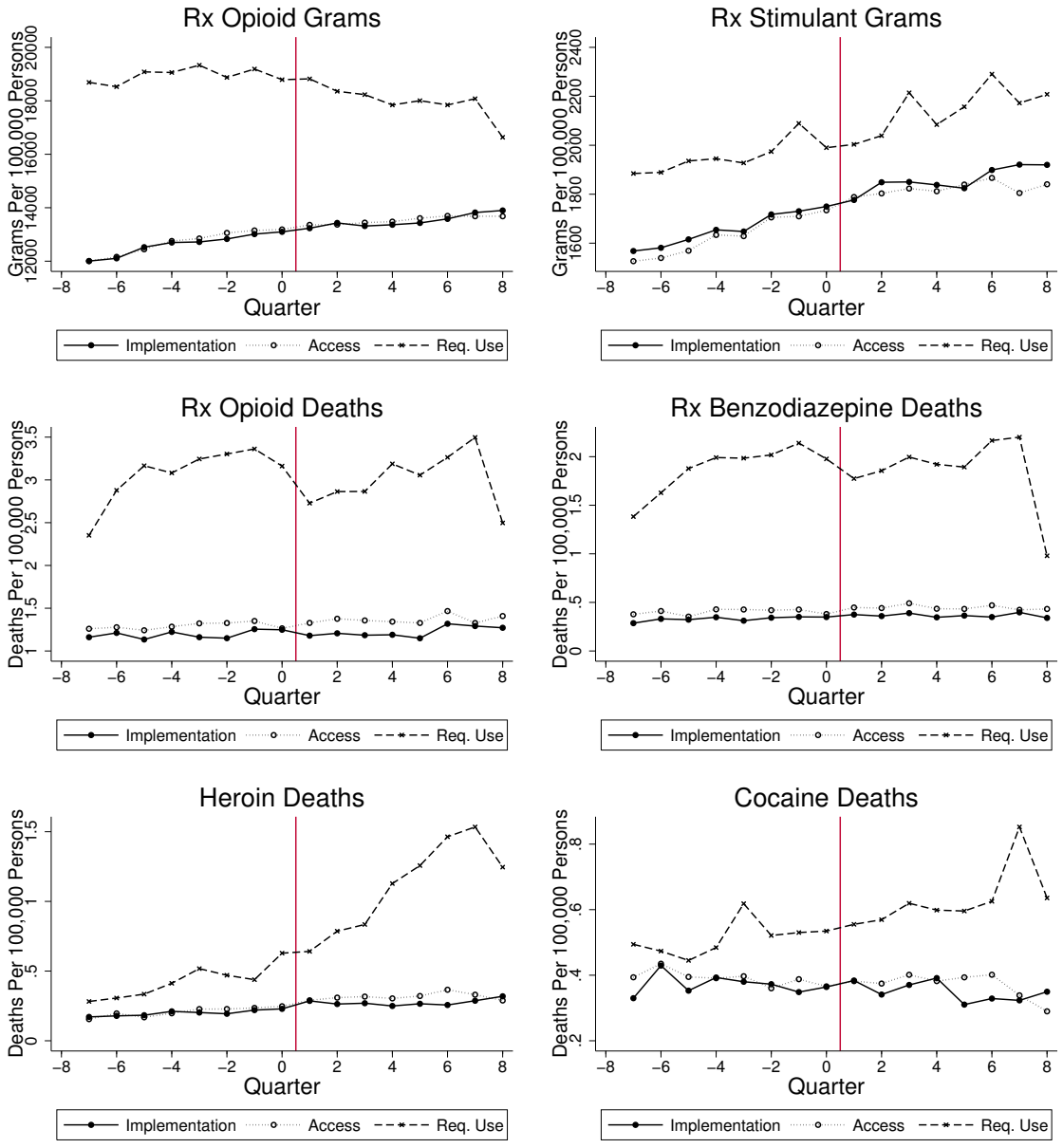

Figure 3: Effect of PDMP Characteristics (2000-2013)

Notes: Drug deaths are drawn from NVSS Mortality Files and drug grams are drawn from ARCOS (see Section II.***A*** for details). Outcomes are divided by 2010 population estimates. Grams are adjusted for potency (see Table 4 in the Appendix). See Section II.***A*** for the active ingredients or ICD-10 codes in each drug class. Panels are not balanced. Florida is dropped (see Section II.***B***).

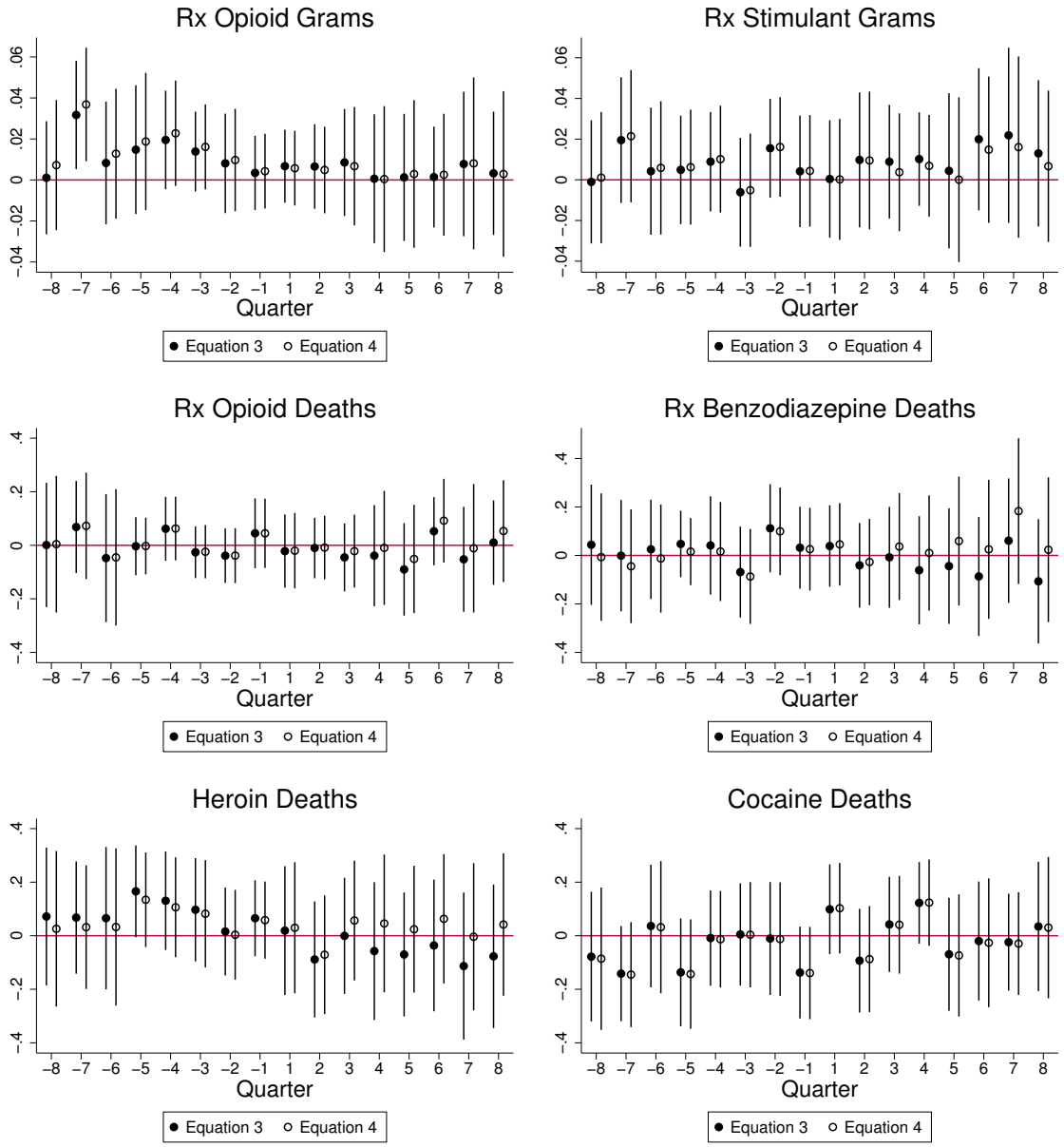

Figure 4: Effect of PDMP Implementation (2000-2013)

Notes: Estimates and 95% confidence intervals are based on the event study approach in Equations 3 and 4. The reference quarter is $j = 0$, the period right before PDMP implementation. Drug deaths are drawn from NVSS Mortality Files and drug grams are drawn from ARCOS (see Section II.***A*** for details). Grams are adjusted for potency (see Table 4 in the Appendix). See Section II.***A*** for the active ingredients or ICD-10 codes in each drug class. Florida is dropped (see Section II.***B***).

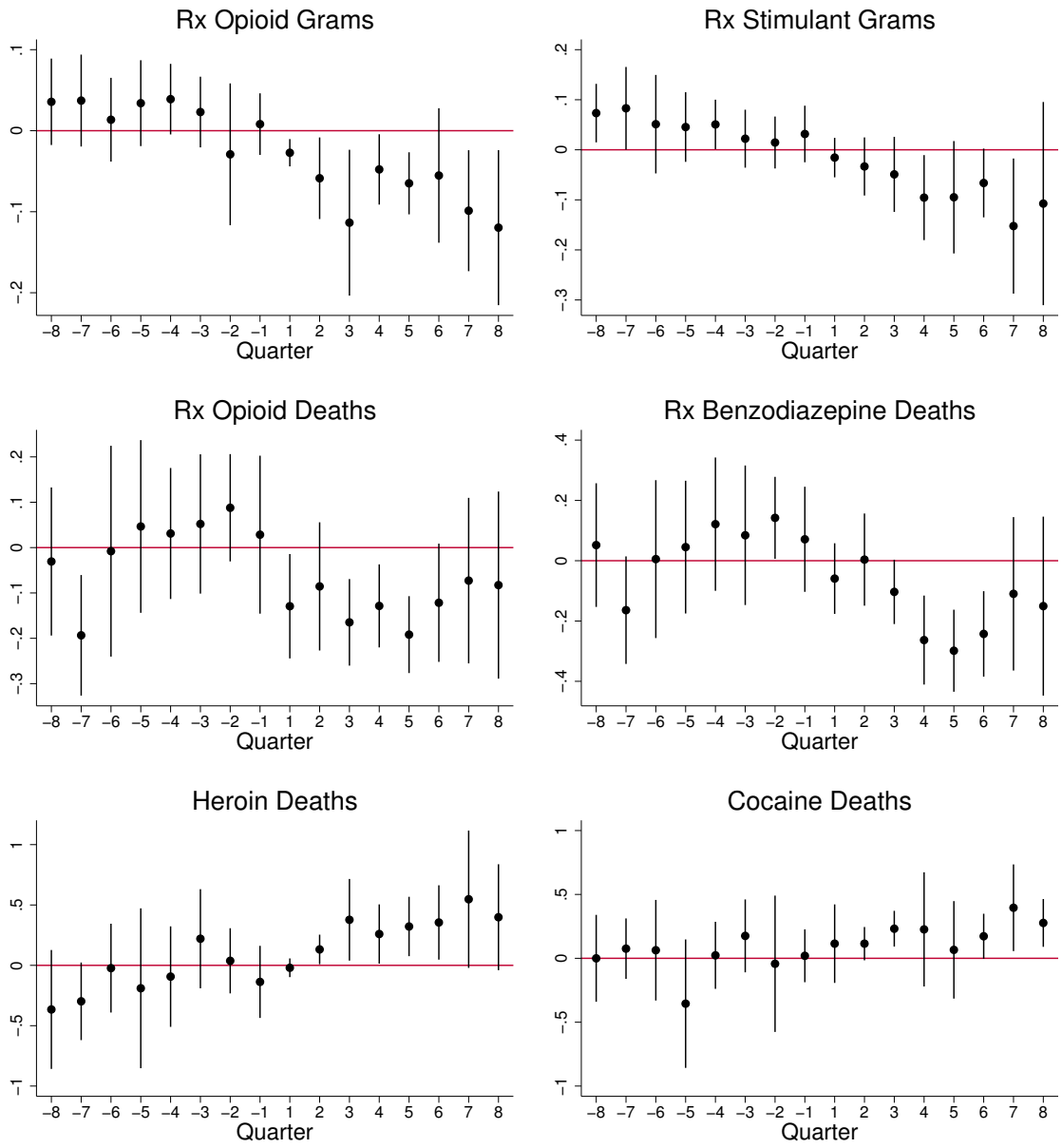

Figure 5: Effect of Required PDMP Use (2000-2013)

Notes: Estimates and 95% confidence intervals are based on the event study approach in Equation 4. The reference quarter is $j = 0$, the period right before required use laws became effective. Drug deaths are drawn from NVSS Mortality Files and drug grams are drawn from ARCOS (see Section II.***A*** for details). Grams are adjusted for potency (see Table 4 in the Appendix). See Section II.***A*** for the active ingredients or ICD-10 codes in each drug class. Florida is dropped (see Section II.***B***).

Table 1: Effect of PDMP Implementation (2000-2013)

Panel A: Quarterly Drug Grams												
	Rx Opioid Grams						Rx Stimulant Grams					
$PDMP$	0.02	-0.01	-0.01	-0.01	-0.02	-0.03	0.02	0.01	0.00	0.00	0.01	0.00
	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
R^2	0.95	0.96	0.97	0.97			0.94	0.94	0.96	0.96		
$Mean$	380,466	380,466	380,466	380,466	380,466	380,466	53,414	53,414	53,414	53,414	53,414	53,414
Panel B: Quarterly Drug Deaths												
	Rx Opioid Deaths						Rx Benzo. Deaths					
$PDMP$	-0.06	-0.03	-0.02	-0.01	-0.02	-0.01	-0.13	-0.05	0.04	0.04	0.02	0.03
	(0.07)	(0.07)	(0.08)	(0.08)	(0.06)	(0.05)	(0.08)	(0.07)	(0.09)	(0.09)	(0.11)	(0.10)
R^2	0.57	0.57	0.65	0.65			0.48	0.48	0.58	0.58		
$Mean$	35.76	35.76	35.76	35.76	35.76	35.76	9.78	9.78	9.78	9.78	9.78	9.78
	Heroin Deaths						Cocaine Deaths					
$PDMP$	-0.21*	-0.13	-0.03	-0.03	0.06	0.09	0.05	0.06	0.08	0.07	-0.03	-0.03
	(0.12)	(0.08)	(0.09)	(0.09)	(0.19)	(0.18)	(0.05)	(0.06)	(0.07)	(0.07)	(0.09)	(0.09)
R^2	0.45	0.45	0.65	0.65			0.20	0.20	0.30	0.31		
$Mean$	8.36	8.36	8.36	8.36	8.36	8.36	15.53	15.53	15.53	15.53	15.53	15.53
N	2,800	2,800	2,800	2,800	2,800	2,800	2,800	2,800	2,800	2,800	2,800	2,800
$Clusters$	50	50	50	50	50	50	50	50	50	50	50	50
$State\ F.E.$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$Year\ F.E.$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$Quarter\ F.E.$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$State\ Trends$	No	No	Yes	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Yes
$All\ Years$	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
$+/-2\ Years$	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
$ln(Y_{st})$	Yes	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Yes	No	No
$Poisson$	No	No	No	No	Yes	Yes	No	No	No	No	Yes	Yes

Notes: Grams are drawn from ARCOS Report 2 and deaths are drawn from NVSS Mortality Files (see Section II.***A*** for details). See Section II.***A*** for the active ingredients or ICD-10 codes in each drug class. Grams are adjusted for potency (see Table 4 in the Appendix). The unit of analysis is a state-quarter. $ln(Y_{st})$ identifies estimates based on the log transformation of the outcome, while *Poisson* identifies estimates based on the generalized linear model with Poisson distribution and log link function. $+/-2\ Years$ identifies the effect of PDMP implementation in the two years pre/post. *Mean* is level mean when PDMP=0. All regressions control for the log of population. Florida is dropped (see Section II.***B***). State clustered standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 2: Effect of Direct PDMP Access (2000-2013)

Panel A: Quarterly Drug Grams								
	Rx Opioid Grams				Rx Stimulant Grams			
PDMP	-0.01	-0.01	-0.02	-0.02	-0.02	-0.02	-0.01	-0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Direct Access	0.00	0.00	-0.00	-0.00	0.03	0.02	0.02	0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
R^2	0.97	0.97			0.96	0.96		
Mean	380,466	380,466	380,466	380,466	53,414	53,414	53,414	53,414
Panel B: Quarterly Drug Deaths								
	Rx Opioid Deaths				Rx Benzo. Deaths			
PDMP	-0.01	-0.03	-0.03	-0.04	0.07	0.06	0.04	0.06
	(0.09)	(0.08)	(0.07)	(0.06)	(0.08)	(0.08)	(0.11)	(0.11)
Direct Access	-0.00	0.00	0.01	0.01	-0.04	-0.04	-0.03	-0.03
	(0.05)	(0.05)	(0.04)	(0.04)	(0.06)	(0.06)	(0.06)	(0.06)
R^2	0.65	0.65			0.58	0.58		
Mean	35.76	35.76	35.76	35.76	9.78	9.78	9.78	9.78
	Heroin Deaths				Cocaine Deaths			
PDMP	0.00	0.00	0.09	0.08	0.07	0.04	-0.07	-0.08
	(0.10)	(0.10)	(0.18)	(0.17)	(0.07)	(0.07)	(0.10)	(0.09)
Direct Access	-0.05	-0.04	-0.05	-0.04	0.02	0.02	0.07	0.06
	(0.10)	(0.09)	(0.08)	(0.08)	(0.05)	(0.05)	(0.05)	(0.05)
R^2	0.65	0.65			0.30	0.30		
Mean	8.36	8.36	8.36	8.36	15.53	15.53	15.53	15.53
N	2,800	2,800	2,800	2,800	2,800	2,800	2,800	2,800
Clusters	50	50	50	50	50	50	50	50
State F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
All Years	Yes	No	Yes	No	Yes	No	Yes	No
$+/-2$ *Years*	No	Yes	No	Yes	No	Yes	No	Yes
$ln(Y_{st})$	Yes	Yes	No	No	Yes	Yes	No	No
Poisson	No	No	Yes	Yes	No	No	Yes	Yes

Notes: Grams are drawn from ARCOS Report 2 and deaths are drawn from NVSS Mortality Files (see Section II.***A*** for details). See Section II.***A*** for the active ingredients or ICD-10 codes in each drug class. Grams are adjusted for potency (see Table 4 in the Appendix). The unit of analysis is a state-quarter. $ln(Y_{st})$ identifies estimates based on the log transformation of the outcome, while *Poisson* identifies estimates based on the generalized linear model with Poisson distribution and log link function. $+/-2$ *Years* identifies the effect of direct PDMP access in the two years pre/post. *Mean* is level mean when PDMP=0. All regressions control for the log of population. Florida is dropped (see Section II.***B***). State clustered standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Effect of Required PDMP Use (2000-2013)

Panel A: Quarterly Drug Grams								
	Rx Opioid Grams				Rx Stimulant Grams			
$PDMP$	-0.01	-0.01	-0.03	-0.03	-0.00	-0.01	-0.01	-0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
$Req.\ Use$	-0.09***	-0.08***	-0.11***	-0.10***	-0.11**	-0.10**	-0.14**	-0.13**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.06)	(0.05)	(0.06)	(0.06)
R^2	0.97	0.97			0.96	0.96		
$Mean$	380,466	380,466	380,466	380,466	53,414	53,414	53,414	53,414
Panel B: Quarterly Drug Deaths								
	Rx Opioid Deaths				Rx Benzo. Deaths			
$PDMP$	-0.02	-0.01	-0.03	-0.02	0.03	0.04	0.00	0.03
	(0.08)	(0.08)	(0.06)	(0.06)	(0.09)	(0.09)	(0.11)	(0.10)
$Req.\ Use$	-0.09	-0.13***	-0.10**	-0.11***	-0.13	-0.17**	-0.14*	-0.13*
	(0.06)	(0.04)	(0.04)	(0.03)	(0.12)	(0.08)	(0.08)	(0.08)
R^2	0.65	0.65			0.58	0.59		
$Mean$	35.76	35.76	35.76	35.76	9.78	9.78	9.78	9.78
	Heroin Deaths				Cocaine Deaths			
$PDMP$	-0.01	-0.00	0.07	0.08	0.08	0.08	-0.01	-0.01
	(0.09)	(0.09)	(0.18)	(0.18)	(0.07)	(0.07)	(0.09)	(0.09)
$Req.\ Use$	0.40**	0.33***	0.11	0.11	0.12	0.18*	0.15**	0.15***
	(0.16)	(0.12)	(0.08)	(0.08)	(0.10)	(0.10)	(0.06)	(0.05)
R^2	0.65	0.65			0.30	0.30		
$Mean$	8.36	8.36	8.36	8.36	15.53	15.53	15.53	15.53
N	2,800	2,800	2,800	2,800	2,800	2,800	2,800	2,800
$Clusters$	50	50	50	50	50	50	50	50
$State\ F.E.$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$Year\ F.E.$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$Quarter\ F.E.$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$State\ Trends$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$All\ Years$	Yes	No	Yes	No	Yes	No	Yes	No
$+/-2\ Years$	No	Yes	No	Yes	No	Yes	No	Yes
$ln(Y_{st})$	Yes	Yes	No	No	Yes	Yes	No	No
$Poisson$	No	No	Yes	Yes	No	No	Yes	Yes

Notes: Grams are drawn from ARCOS Report 2 and deaths are drawn from NVSS Mortality Files (see Section II.***A*** for details). See Section II.***A*** for the active ingredients or ICD-10 codes in each drug class. Grams are adjusted for potency (see Table 4 in the Appendix). The unit of analysis is a state-quarter. $ln(Y_{st})$ identifies estimates based on the log transformation of the outcome, while *Poisson* identifies estimates based on the generalized linear model with Poisson distribution and log link function. $+/-2\ Years$ identifies the effect of required PDMP use in the two years pre/post. *Mean* is level mean when PDMP=0. All regressions control for the log of population. Florida is dropped (see Section II.***B***). State clustered standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

A Appendix

A.*A* Other Graphs and Tables

Table 4: Dose Equivalence

Drug	Route	Mg	Drug	Route	Mg
Panel A: Opioids					
Oxycodone	Oral	20	Methadone (30-90)	Oral	7.5
Fentanyl	Transdermal	0.36	Methadone (90-300)	Oral	5
Oxymorphone	Oral	10	Methadone (>300)	Oral	3.75
Oxymorphone	IV	1	Hydrocodone	Oral	30
Morphine	Oral	30	Hydromorphone	Oral	7.5
Morphine	IV	10	Hydromorphone	IV	1.5
Codeine	Oral	200	Meperidine	Oral	300
Codeine	IV	100	Meperidine	IV	100
Panel B: Stimulants					
Amphetamine	Oral	5	Methylphenidate	Oral	10

Notes: Table 4 lists the dose equivalence in milligrams for active ingredients in the opioid and stimulant drug classes. The dose equivalence in Panel A was drawn from McPherson (2009) and was used to convert different active ingredients in the opioid class into oxycodone potency units. The dose equivalence in Panel B was drawn from ADHD Medication Calculator (http://www.adhdmedcalc.com) and was used to convert different active ingredients in the stimulant class into amphetamine potency units. Note that the equivalence changes not only by active ingredient, but also by formulation. Since ARCOS data provides total gram information by active ingredient, but does not specify a formulation, this study assumes oral doses when possible and transdermal doses when not.

Table 5: PDMP Implementation

	Author		NAMSL		TTAC			Author		NAMSL		TTAC	
State	Year	Mo.	Year	Mo.	Year	Mo.	State	Year	Mo.	Year	Mo.	Year	Mo.
Alabama[1,2,3]	2006	4	2006	4	2006	N/A	Montana[1,2]	2012	3	2012	3	2012	N/A
Alaska[1,2]	2011	8	2011	8	2011	N/A	Nebraska[1,2]	2011	4	N/A	N/A	2011	N/A
Arizona[1,2,3]	2008	10	2008	10	2008	N/A	Nevada	1997	1	1997	1	1997	N/A
Arkansas[1]	2013	3	2013	3	2013	N/A	N. Hampshire	2014	7	N/A	N/A	2014	N/A
California	1939	N/A	1998	N/A	1939	N/A	New Jersey[1,2]	2011	9	2011	9	2011	N/A
Colorado[1,2,3]	2007	7	2007	7	2007	N/A	New Mexico[1,2,3]	2005	8	2005	1	2005	N/A
Connecticut[1,2,3]	2008	7	2008	7	2008	N/A	New York	1973	4	N/A	N/A	1973	N/A
Delaware[1,2]	2012	3	2012	3	2012	N/A	N. Carolina[1,2,3]	2007	7	2007	7	2007	N/A
Florida[1,2]	2011	9	2011	9	2011	N/A	N. Dakota[1,2,3]	2007	9	2007	1	2007	N/A
Georgia	2013	5	2013	7	2013	N/A	Ohio[1,2,3]	2006	7	2006	1	2006	N/A
Hawaii	1943	N/A	N/A	N/A	1943	N/A	Oklahoma	1991	N/A	1990	N/A	1991	N/A
Idaho	1998	10	1997	N/A	1967	N/A	Oregon[1,2]	2011	6	2011	6	2011	N/A
Illinois	1957	N/A	N/A	N/A	1968	N/A	Pennsylvania	1973	N/A	N/A	N/A	1973	N/A
Indiana	1994	N/A	1994	N/A	1998	N/A	R. Island	1979	N/A	N/A	N/A	1979	N/A
Iowa[1,2,3]	2009	3	2009	1	2009	N/A	S. Carolina[1,2,3]	2008	2	2008	2	2008	N/A
Kansas[1,2,3]	2011	2	2011	2	2011	N/A	S. Dakota[1,2]	2011	12	2011	N/A	2011	N/A
Kentucky	1999	N/A	1999	1	1999	N/A	Tennessee[1,2,3]	2006	12	N/A	N/A	2006	N/A
Louisiana[1,2,3]	2008	8	2008	6	2008	N/A	Texas	1982	7	N/A	N/A	1982	N/A
Maine[1,2,3]	2004	7	2004	7	2004	N/A	Utah	1995	7	1997	1	1996	N/A
Maryland	2013	8	2013	8	2013	N/A	Vermont[1,2,3]	2009	1	2009	1	2009	N/A
Mass.	1992	4	N/A	N/A	1994	N/A	Virginia[1,2,3]	2006	6	2006	6	2003	N/A
Michigan	1988	1	2003	1	1989	N/A	Washington[1,2]	2011	10	2011	10	2011	N/A
Minnesota[1,2,3]	2010	1	2010	1	2010	N/A	W. Virginia	1996	N/A	N/A	N/A	1995	N/A
Mississippi[1,2,3]	2005	12	2005	N/A	2005	N/A	Wisconsin	2013	6	2013	5	2013	N/A
Missouri	N/A	N/A	N/A	N/A	N/A	N/A	Wyoming[1,2,3]	2004	10	2004	N/A	2004	N/A

Notes: Table is constructed using information collected by the author, the National Alliance for Model State Laws (http://www.namsdl.org/library/1667DC6B-65BE-F4BB-AB7F08135A3A7174/), and the Prescription Drug Monitoring Program Training and Technical Assistance Center at Brandeis University (http://www.pdmpassist.org/content/state-profiles). Superscripts 1, 2, and 3 identify states with balanced panels at +/- 1 year, +/- 2 year, and +/- 3 year time windows as specified in Figures 2 and 6.

Table 6: PDMP Access

	Author		NAMSL			Author		NAMSL	
State	Year	Mo.	Year	Mo.	State	Year	Mo.	Year	Mo.
Alabama	2007	8	2007	8	Montana	2012	11	2012	10
Alaska	2012	1	2012	1	Nebraska	2011	4	N/A	N/A
Arizona	2008	12	2008	12	Nevada	1997	4	97	4
Arkansas	2013	3	2013	3	New Hampshire	2014	7	N/A	N/A
California	2009	9	2009	N/A	New Jersey	2012	1	2012	1
Colorado	2008	2	2008	2	New Mexico	2012	N/A	2005	8
Connecticut	2008	7	N/A	N/A	New York	2010	3	N/A	N/A
Delaware	2012	8	2012	8	North Carolina	2007	10	2007	10
Florida	2011	10	2011	10	North Dakota	2008	3	N/A	N/A
Georgia	2013	5	2013	7	Ohio	2006	10	2006	10
Hawaii	N/A	N/A	N/A	N/A	Oklahoma	2006	11	2006	7
Idaho	2007	7	1998	N/A	Oregon	2011	9	2011	9
Illinois	2008	1	N/A	N/A	Pennsylvania	2016	8	N/A	N/A
Indiana	2007	1	2007	N/A	Rhode Island	2012	9	N/A	N/A
Iowa	2009	3	2009	3	South Carolina	2008	6	2008	6
Kansas	2011	4	2011	4	South Dakota	2012	3	2012	3
Kentucky	2005	3	1999	7	Tennessee	2006	12	N/A	N/A
Louisiana	2009	1	2009	1	Texas	2012	8	N/A	N/A
Maine	2005	1	2005	1	Utah	2004	N/A	1997	1
Maryland	2013	8	2014	1	Vermont	2009	4	2009	4
Massachusetts	2010	12	N/A	N/A	Virginia	2009	9	2006	6
Michigan	2007	4	2003	2	Washington	2012	1	2012	1
Minnesota	2010	4	2010	4	West Virginia	2004	12	N/A	N/A
Mississippi	2008	N/A	2005	12	Wisconsin	2013	6	2013	5
Missouri	N/A	N/A	N/A	N/A	Wyoming	2013	7	2004	N/A

Notes: Table is constructed using information collected by the author and the National Alliance for Model State Laws (http://www.namsdl.org/library/1667DC6B-65BE-F4BB-AB7F08135A3A7174/). The author collected dates of *direct* access, while NAMSL collected dates of access generally defined. In the few instances where PDMP administrators could not be reached, NAMSL dates were used.

Table 7: Effective Dates of Required PDMP Use State Laws as of 2013

	Author		TTAC		PSP	
State	Year	Mo.	Year	Mo.	Year	Mo.
Kentucky	2012	7	2012	7	N/A	N/A
New York	2013	8	2013	8	N/A	N/A
Ohio	2011	10	2011	10	2011	11
Tennessee	2013	4	2013	4	N/A	N/A
Oklahoma	2010	11	2010	N/A	2010	11
Nevada*	2007	10	2009	N/A	2011	10
Delaware*	2012	3	N/A	N/A	2011	1
Louisiana**	2014	8	N/A	N/A	2010	9
New Mexico**	2017	1	2012-16	N/A	N/A	N/A
West Virginia**	2012	6	2013	N/A	N/A	N/A

Notes: Based on data collected by the author, NAMSDL (2011, 2014), TTAC (2016), and PSP (2011).
*TTAC identified Nevada and Delaware as having "subjective" laws (TTAC, 2016) and thus, these were not included in the treatment group. Nevada's law stated that *"A practitioner shall, before writing a prescription for a controlled substance listed in schedule II, III or IV for a patient, obtain a patient utilization report regarding the patient for the preceding 12 months from the computerized program ... if the practitioner has a reasonable belief that the patient may be seeking the controlled substance, in whole or in part, for any reason other than the treatment of an existing medical condition"*. Similarly, Delaware's law stated that *"A prescriber, or other person authorized by the prescriber, shall obtain, before writing a prescription for a controlled substance listed in Schedule II, III, IV or V for a patient, a patient utilization report regarding the patient for the preceding 12 months from the computerized program ... when the prescriber has a reasonable belief that the patient may be seeking the controlled substance, in whole or in part, for any reason other than the treatment of an existing medical condition."* For robustness, an analysis that incorporates both states is conducted (Table 9 in the Appendix).
**States with plausible alternative effective dates due to the evolution of the law included Louisiana, New Mexico, and West Virginia. PSP lists Louisiana as having originally implemented a law in September 2010. However, the original law regulated pain clinics (§ 7831) and its only allusion to required PDMP use stated that *"The medical director [of a clinic] is responsible for applying to access and query the Louisiana Prescription Monitoring Program (PMP)"*. Official documentation from the state of Louisiana associates (§ 7831) with January 2008. Due to its limited scope and wording regarding required use ("is responsible for") (§ 7831) is not considered the effective date of Louisiana's required use law. PDMP administrators in this state confirmed this and also reported that (§ 7831) only affected a handful of providers. They noted that in August 2014, Louisiana did implement a required use law (LA RS §40:978) which stated that *"A prescriber shall access the Prescription Monitoring Program prior to initially prescribing any Schedule II controlled dangerous substance to a patient for the treatment of non-cancer-related chronic or intractable pain."* For robustness, the alternative date January 2008 is used (Table 10 in the Appendix).
TTAC lists New Mexico as originally implementing a required PDMP use mandate between 2012-16. However, after reaching out to PDMP administrators in this state to inquire about the exact effective date of the state law, they reported it (§ 26-1-16.1) became effective in January 1, 2017. They also clarified that the different professional licensing boards began regulating how their licensees were to use the PDMP at different points in time between 2012-14 (e.g. the medical board in September 2012, the dentistry board in July 2013, the optometry board in April 2014, etc.). For robustness, the alternative date September 2012 is used (Table 10 in the Appendix).
NAMSL documentation (NAMSDL, 2011) shows that prior to 2012, West Virginia had a law regulating Toxicology Screens in Opioid Treatment Programs (OTP) which alluded to required PDMP use (§ 64-90-40). This law became effective in April 2008 and stated that *"The program shall comply with policies and procedures developed by the designated state oversight agency...to allow access to the Prescription Drug Registry...: 40.16.a. Before the administration of methadone or other treatment in an OTP; 40.16.b. After any positive drug test; and 40.16.c. At each ninety-day treatment review. 40.17. Each Prescription Drug Registry access shall confirm that the patient is not seeking prescription medication from multiple sources."* Due to its limited scope and wording regarding required use ("to allow access to"), (§ 64-90-40) is not considered West Virginia's required PDMP use law. For robustness, the alternative date April 2008 is used (Table 10 in the Appendix).

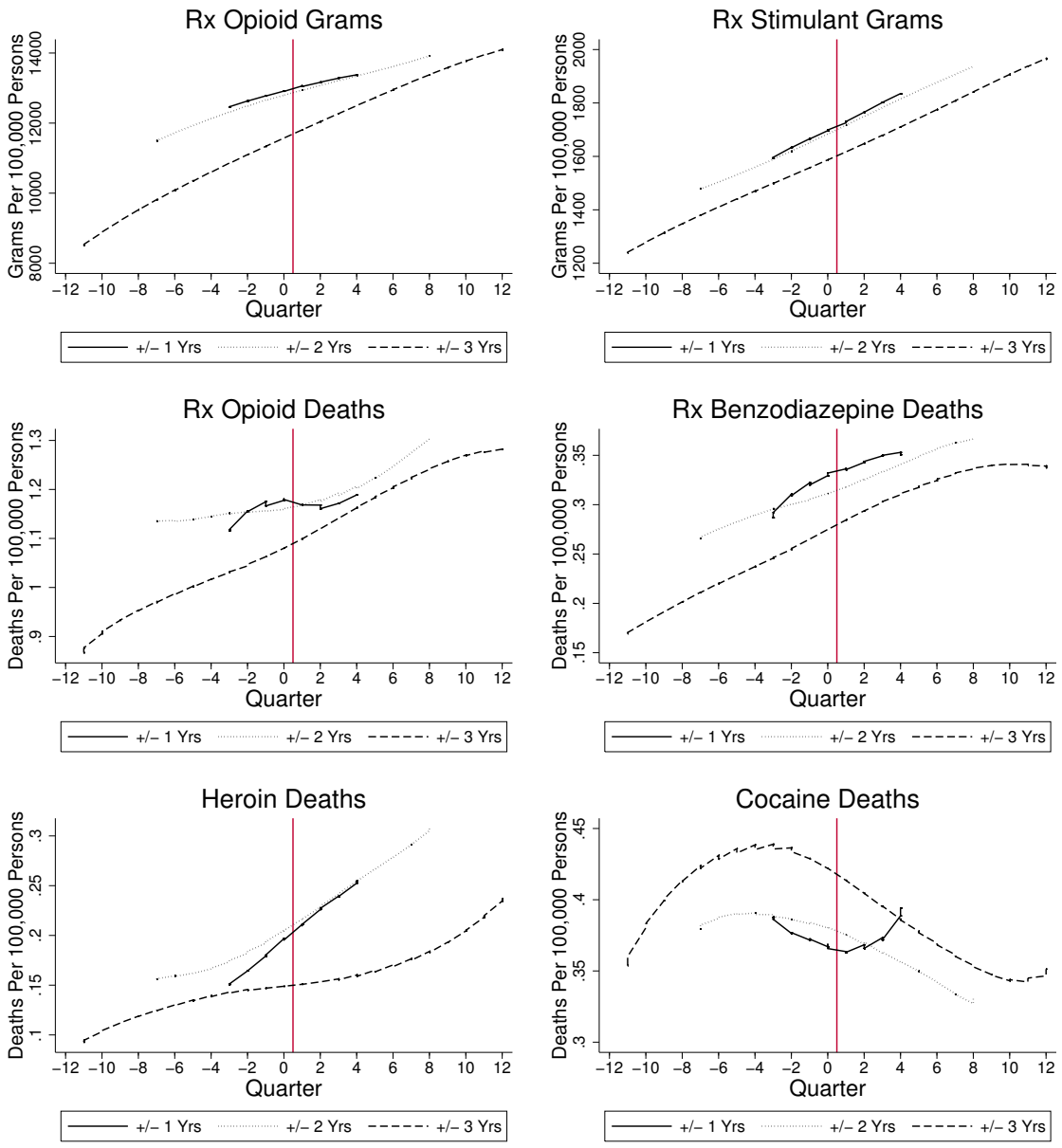

Figure 6: Effect of PDMP Implementation (2000-2013)

Notes: Figure is constructed using locally weighted regression with bandwidth of 0.8. Drug deaths are drawn from NVSS Mortality Files and drug grams are drawn from ARCOS (see Section II.***A*** for details). Grams are divided by 2010 population estimates and adjusted for potency (see Table 4 in the Appendix). See Section II.***A*** for the active ingredients or ICD-10 codes in each drug class. Graphs are based on a balanced panel of treated states at different pre/post time windows. Florida is dropped (see Section II.***B***).

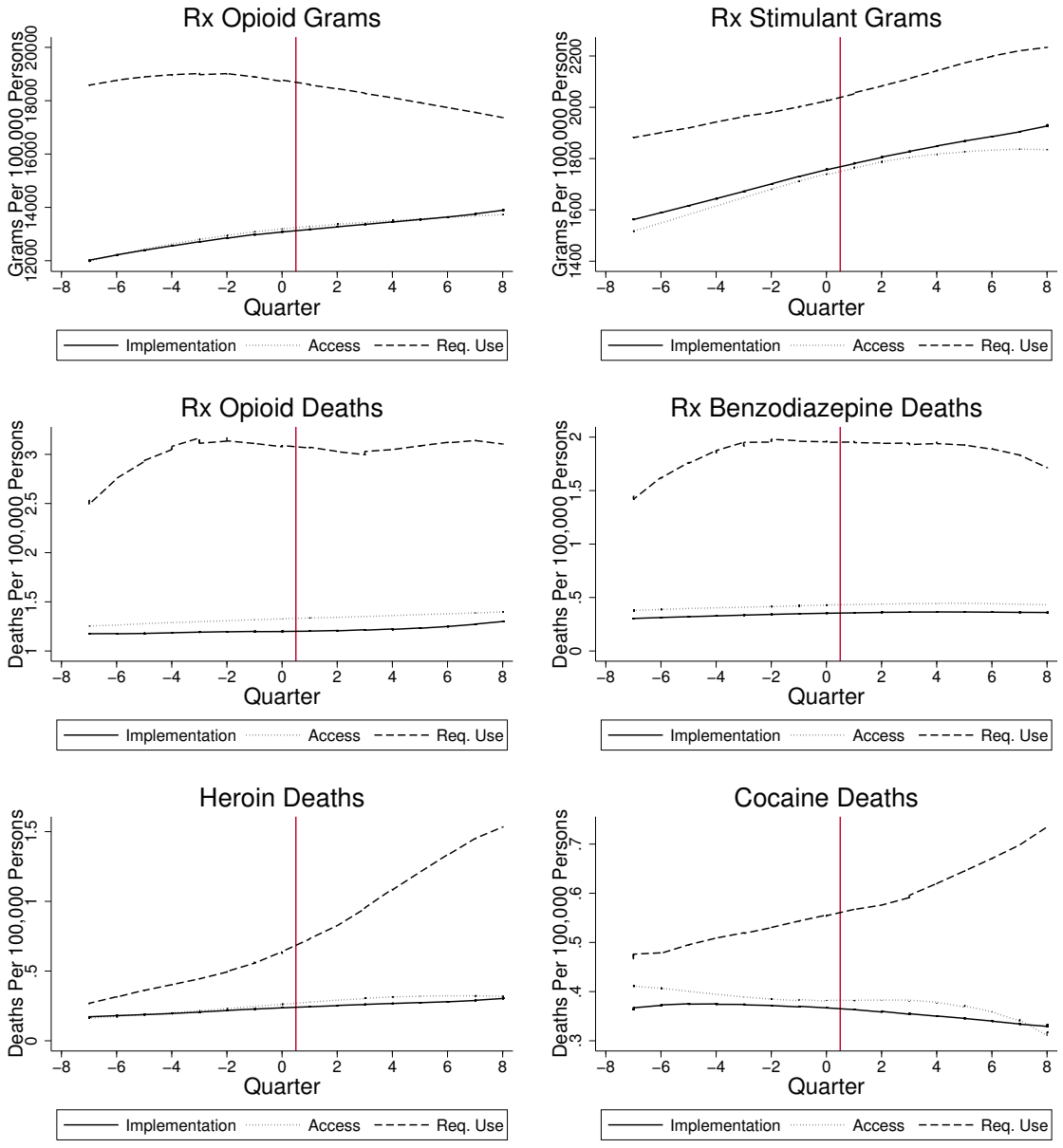

Figure 7: Effect of PDMP Characteristics (2000-2013)

Notes: Figure is constructed using locally weighted regression with bandwidth of 0.8. Drug deaths are drawn from NVSS Mortality Files and drug grams are drawn from ARCOS (see Section II.***A*** for details). Grams are divided by 2010 population estimates and adjusted for potency (see Table 4 in the Appendix). See Section II.***A*** for the active ingredients or ICD-10 codes in each drug class. Panels are not balanced. Florida is dropped (see Section II.***B***).

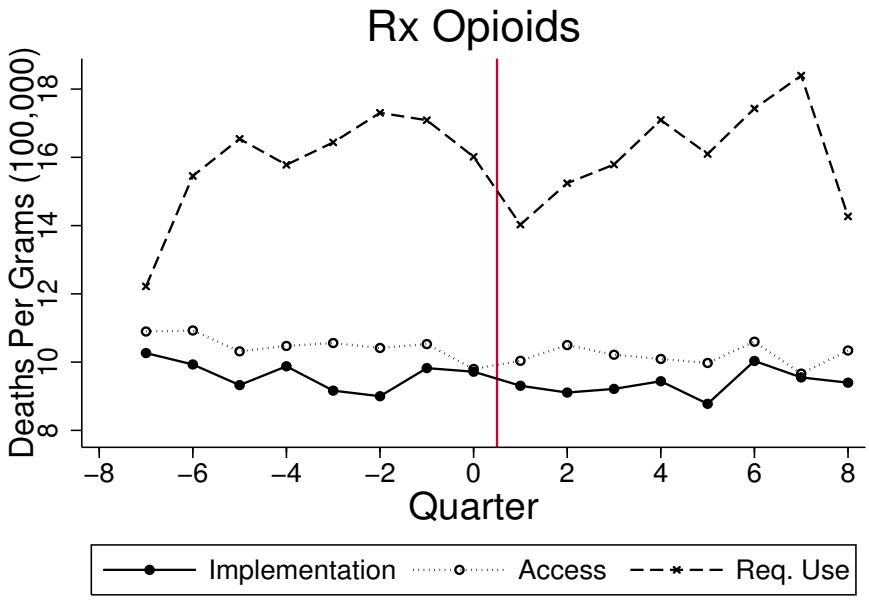

Figure 8: Effect of PDMP Characteristics (2000-2013)

Notes: Drug deaths are drawn from NVSS Mortality Files and drug grams are drawn from ARCOS (see Section II.***A*** for details). Grams are adjusted for potency (see Table 4 in the Appendix). See Section II.***A*** for the active ingredients or ICD-10 codes in each drug class. Panels are not balanced. Florida is dropped (see Section II.***B***).

A.*B* Spillovers

This section explores whether required PDMP use laws in treatment states resulted in spillovers among neighboring states. Neighboring states were defined as any state adjacent to a treatment state.[32] In the presence of spillovers, one could expect an increase in grams or in overdose deaths in neighboring states after the implementation of a required PDMP use law in an adjacent treatment state.

The spillover dummy variable was generated in two ways. First, the spillover dummy variable was generated by assigning each neighboring state the value 1 if the adjacent treatment state had implemented a required PDMP use law at time t and 0 otherwise. All other states were assigned the value 0. Because some neighboring states had more than one adjacent treatment state, each neighboring state was assigned the date of the adjacent treatment state first implementing a required PDMP use law. Second, the spillover dummy variable was generated by replicating all the steps followed in the first way, and in addition, because some neighboring states eventually became treatment states, the spillover variable was assigned the value 0 if a neighboring state had itself implemented a required PDMP use law at time t.[33]

Results from this analysis can be found on Table 8. Panel A shows evidence of spillovers for opioid grams. Specifically, opioid grams purchased by legal suppliers increased by 4% in neighboring states after an adjacent state implemented a required PDMP use law. These findings could be explained by increased demand in neighboring states from residents in treatment states. Panel B shows no evidence of spillovers for overdose deaths. This, however, is not surprising as the consumption of these drugs by treatment state residents need not occur at the neighboring states.[34]

[32] Treatment states are those implementing a required PDMP use law between 2000-13.

[33] We follow both approaches due to heterogeneity in the scope and stringency of required PDMP use laws.

[34] e.g. as prescription drugs can be smuggled from neighboring states into treatment states.

Table 8: Spillover Effects of Required PDMP Use (2000-2013)

Panel A: Quarterly Drug Grams								
	Rx Opioid Grams				Rx Stimulant Grams			
PDMP	-0.01	-0.03	-0.01	-0.03	-0.00	-0.01	-0.00	-0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Req. Use	-0.11***	-0.11***	-0.08***	-0.09***	-0.11**	-0.14**	-0.11*	-0.14**
	(0.02)	(0.02)	(0.03)	(0.02)	(0.06)	(0.06)	(0.06)	(0.06)
Spillover	0.04*	0.03**	0.04**	0.04***	-0.00	0.00	0.01	0.02
	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)
Panel B: Quarterly Drug Deaths								
	Rx Opioid Deaths				Rx Benzo. Deaths			
PDMP	-0.02	-0.03	-0.02	-0.03	0.03	-0.00	0.03	0.00
	(0.08)	(0.06)	(0.08)	(0.06)	(0.09)	(0.11)	(0.09)	(0.11)
Req. Use	-0.07	-0.09**	-0.12**	-0.10***	-0.11	-0.12	-0.17	-0.17**
	(0.07)	(0.04)	(0.06)	(0.04)	(0.14)	(0.09)	(0.12)	(0.08)
Spillover	-0.08	-0.01	-0.09	-0.01	-0.08	-0.08	-0.10	-0.07
	(0.06)	(0.03)	(0.06)	(0.04)	(0.11)	(0.08)	(0.11)	(0.08)
	Heroin Deaths				Cocaine Deaths			
PDMP	-0.01	0.09	-0.01	0.08	0.08	-0.02	0.08	-0.02
	(0.09)	(0.18)	(0.09)	(0.18)	(0.07)	(0.09)	(0.07)	(0.09)
Req. Use	0.40**	0.10	0.39**	0.13*	0.14	0.16**	0.11	0.13*
	(0.15)	(0.08)	(0.17)	(0.08)	(0.11)	(0.06)	(0.11)	(0.07)
Spillover	0.01	0.10	-0.03	0.07	-0.04	-0.06	-0.06	-0.05
	(0.09)	(0.07)	(0.09)	(0.08)	(0.06)	(0.05)	(0.06)	(0.05)
N	2,800	2,800	2,800	2,800	2,800	2,800	2,800	2,800
Clusters	50	50	50	50	50	50	50	50
State F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
All Years	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$ln(Y_{st})$	Yes	No	Yes	No	Yes	No	Yes	No
Poisson	No	Yes	No	Yes	No	Yes	No	Yes
*Way*1	Yes	Yes	No	No	Yes	Yes	No	No
*Way*2	No	No	Yes	Yes	No	No	Yes	Yes

Notes: Grams are drawn from ARCOS Report 2 and deaths are drawn from NVSS Mortality Files (see Section II.***A*** for details). See Section II.***A*** for the active ingredients or ICD-10 codes in each drug class. Grams are adjusted for potency (see Table 4 in the Appendix). The unit of analysis is a state-quarter. $ln(Y_{st})$ identifies estimates based on the log transformation of the outcome, while *Poisson* identifies estimates based on the generalized linear model with Poisson distribution and log link function. $+/-2$ *Years* identifies the effect of required PDMP use in the two years pre/post. All regressions control for the log of population. Florida is dropped (see Section II.***B***). State clustered standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

A.*C* Required PDMP Use

This section considers heterogeneity in the scope and evolution of required PDMP use laws by exploring different types of treatment states. The analysis in Table 9 incorporates states with "subjective" required PDMP use laws into the treatment group (see Section II.***A*** for details). These states are Nevada and Delaware, both of which included a clause stating that a prescriber shall obtain a patient report if the *"prescriber has a reasonable belief that the patient may be seeking the controlled substance, in whole or in part, for any reason other than the treatment of an existing medical condition."* (see notes in Table 7 in the Appendix for details). With a few exceptions, including states with "subjective" required PDMP use laws into the treatment group slightly attenuates the magnitude and statistical significance of the estimates. These findings, however, are expected as "subjective" laws are less likely to have affected prescriber behavior considering that PDMP use remained optional.

The analysis in Table 10 assigns alternative effective dates to those states for which the law evolved over time (see Section II.***A*** for details). These states are Louisiana, New Mexico, and West Virginia (see notes in Table 7 in the Appendix for details). As earlier versions of the law in these states were either weaker, of smaller scope, or there was uncertainty about whether a requirement existed, main findings rely on the effective dates of the more stringent, objective, and overarching version of the laws. This analysis, however, relies on the effective date of the first law or regulation possibly alluding to required PDMP use (see notes in Table 7 in the Appendix for details). As expected, assigning the effective date of the weaker version of the law attenuates the statistical significance of the estimates although the sign of the coefficients is robust.

Table 9: Effect of Required PDMP Use (2000-2013)

Panel A: Quarterly Drug Grams								
	Rx Opioid Grams				Rx Stimulant Grams			
$PDMP$	-0.01	-0.01	-0.03	-0.03	0.00	-0.00	-0.00	-0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
$Req.\ Use$	-0.10***	-0.09***	-0.10***	-0.09***	-0.08*	-0.07*	-0.13**	-0.13**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.05)	(0.04)	(0.06)	(0.05)
R^2	0.97	0.97			0.96	0.96		
$Mean$	380,466	380,466	380,466	380,466	53,414	53,414	53,414	53,414
Panel B: Quarterly Drug Deaths								
	Rx Opioid Deaths				Rx Benzo. Deaths			
$PDMP$	-0.02	-0.01	-0.03	-0.02	0.04	0.05	0.01	0.03
	(0.08)	(0.08)	(0.06)	(0.06)	(0.09)	(0.09)	(0.11)	(0.10)
$Req.\ Use$	-0.04	-0.10*	-0.07	-0.08*	-0.09	-0.16**	-0.12*	-0.12*
	(0.06)	(0.06)	(0.05)	(0.04)	(0.10)	(0.07)	(0.07)	(0.07)
R^2	0.65	0.65			0.58	0.59		
$Mean$	35.76	35.76	35.76	35.76	9.78	9.78	9.78	9.78
	Heroin Deaths				Cocaine Deaths			
$PDMP$	-0.03	-0.01	0.07	0.07	0.08	0.08	-0.01	-0.01
	(0.09)	(0.09)	(0.18)	(0.18)	(0.07)	(0.07)	(0.09)	(0.09)
$Req.\ Use$	0.24	0.16	0.08	0.08	0.18**	0.19**	0.17***	0.17***
	(0.16)	(0.14)	(0.08)	(0.08)	(0.08)	(0.07)	(0.05)	(0.05)
R^2	0.65	0.65			0.30	0.30		
$Mean$	8.36	8.36	8.36	8.36	15.53	15.53	15.53	15.53
N	2,800	2,800	2,800	2,800	2,800	2,800	2,800	2,800
$Clusters$	50	50	50	50	50	50	50	50
$State\ F.E.$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$Year\ F.E.$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$Quarter\ F.E.$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$State\ Trends$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$All\ Years$	Yes	No	Yes	No	Yes	No	Yes	No
$+/-2\ Years$	No	Yes	No	Yes	No	Yes	No	Yes
$ln(Y_{st})$	Yes	Yes	No	No	Yes	Yes	No	No
$Poisson$	No	No	Yes	Yes	No	No	Yes	Yes

Notes: Treatment group includes states with "subjective" required PDMP use laws (see notes in Table 7 in the Appendix for details). Grams are drawn from ARCOS Report 2 and deaths are drawn from NVSS Mortality Files (see Section II.***A*** for details). See Section II.***A*** for the active ingredients or ICD-10 codes in each drug class. Grams are adjusted for potency (see Table 4 in the Appendix). The unit of analysis is a state-quarter. $ln(Y_{st})$ identifies estimates based on the log transformation of the outcome, while $Poisson$ identifies estimates based on the generalized linear model with Poisson distribution and log link function. $+/-2\ Years$ identifies the effect of required PDMP use in the two years pre/post. $Mean$ is level mean when PDMP=0. All regressions control for the log of population. Florida is dropped (see Section II.***B***). State clustered standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 10: Effect of Required PDMP Use (2000-2013)

Panel A: Quarterly Drug Grams								
	Rx Opioid Grams				Rx Stimulant Grams			
$PDMP$	-0.01	-0.01	-0.03	-0.03	-0.00	-0.00	-0.00	-0.00
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
$Req.\ Use$	-0.11***	-0.10***	-0.11***	-0.10***	-0.06	-0.05	-0.12*	-0.11**
	(0.03)	(0.02)	(0.02)	(0.02)	(0.04)	(0.04)	(0.06)	(0.06)
R^2	0.97	0.97			0.96	0.96		
$Mean$	380,466	380,466	380,466	380,466	53,414	53,414	53,414	53,414
Panel B: Quarterly Drug Deaths								
	Rx Opioid Deaths				Rx Benzo. Deaths			
$PDMP$	-0.02	-0.02	-0.03	-0.02	0.03	0.04	0.01	0.03
	(0.08)	(0.09)	(0.06)	(0.06)	(0.09)	(0.09)	(0.11)	(0.11)
$Req.\ Use$	-0.15	-0.17	-0.08	-0.09	-0.22	-0.24	-0.10	-0.10
	(0.15)	(0.14)	(0.06)	(0.06)	(0.20)	(0.19)	(0.10)	(0.09)
R^2	0.65	0.65			0.58	0.59		
$Mean$	35.76	35.76	35.76	35.76	9.78	9.78	9.78	9.78
	Heroin Deaths				Cocaine Deaths			
$PDMP$	-0.02	-0.00	0.07	0.07	0.08	0.07	-0.02	-0.02
	(0.09)	(0.09)	(0.18)	(0.18)	(0.07)	(0.07)	(0.09)	(0.09)
$Req.\ Use$	0.16	0.09	0.06	0.06	0.02	0.06	0.08	0.09
	(0.17)	(0.14)	(0.08)	(0.08)	(0.13)	(0.13)	(0.09)	(0.08)
R^2	0.65	0.65			0.30	0.30		
$Mean$	8.36	8.36	8.36	8.36	15.53	15.53	15.53	15.53
N	2,800	2,800	2,800	2,800	2,800	2,800	2,800	2,800
$Clusters$	50	50	50	50	50	50	50	50
$State\ F.E.$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$Year\ F.E.$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$Quarter\ F.E.$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$State\ Trends$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$All\ Years$	Yes	No	Yes	No	Yes	No	Yes	No
$+/-2\ Years$	No	Yes	No	Yes	No	Yes	No	Yes
$ln(Y_{st})$	Yes	Yes	No	No	Yes	Yes	No	No
$Poisson$	No	No	Yes	Yes	No	No	Yes	Yes

Notes: States in treatment group are assigned the effective date of the first law or regulation possibly alluding to required PDMP use (see notes in Table 7 in the Appendix for details). Grams are drawn from ARCOS Report 2 and deaths are drawn from NVSS Mortality Files (see Section II.***A*** for details). See Section II.***A*** for the active ingredients or ICD-10 codes in each drug class. Grams are adjusted for potency (see Table 4 in the Appendix). The unit of analysis is a state-quarter. $ln(Y_{st})$ identifies estimates based on the log transformation of the outcome, while *Poisson* identifies estimates based on the generalized linear model with Poisson distribution and log link function. $+/-2\ Years$ identifies the effect of required PDMP use in the two years pre/post. *Mean* is level mean when PDMP=0. All regressions control for the log of population. Florida is dropped (see Section II.***B***). State clustered standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.